

**RISK PERCEPTION AND WILLINGNESS TO PAY FOR REMOVING
ARSENIC IN DRINKING WATER**

A Thesis

by

SIHONG CHEN

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

August 2011

Major Subject: Agricultural Economics

Risk Perception and Willingness to Pay for Removing
Arsenic in Drinking Water
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Approved by:

Co-Chairs of Committee,	W. Douglass Shaw
	Alexander L. Brown
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ABSTRACT

Risk Perception and Willingness to Pay for Removing
Arsenic in Drinking Water. (August 2011)

Sihong Chen, B.A., South China Agricultural University

Co-Chairs of Advisory Committee: Dr. W. Douglass Shaw
Dr. Alexander L. Brown

This thesis is concerned with (i) how to estimate the perceived mortality risk, (ii) how to calculate the welfare change of mortality risk reduction and (iii) whether ambiguity aversion influences subjects' treatment decision. This study is an important topic in environmental and resource economics, and the attempt to introduce ambiguity preference into the models might shed light on future research in nonmarket valuation.

In this study, I estimate the economic value of reducing mortality risk relating to arsenic in drinking water employing contingent valuation in U.S. arsenic hot spots. Recent studies have shown that perceived risk is a more reliable variable than scientific assessments of risk when applied to interpret and predict individual's averting behavior. I am also interested in the confidence level of perceived risk, which was elicited and treated as the degree of risk ambiguity in this paper. I develop a formal parametric model to calculate the mean willingness to pay (WTP) for mortality risk reduction, and find weak evidence of ambiguity aversion.

DEDICATION

This thesis is dedicated to:

my parents, Jinzhi Chen and Lanwa Li;

my grandmother, Jianxin Zhang;

my aunt Jinling (Linda) Chen;

my friends, Tianyu Deng, Beier Lin and Yu Zhang;

in memory of my grandparents Lieqing Chen, Huizhen He and Shaoye Li.

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Thanks also go to my friends and colleagues and the department faculty and staff for making my graduate study at Texas A&M University an invaluable experience. Finally, thanks to my mother and father for their love, encouragement and financial support in my two-year master study in United States.

TABLE OF CONTENTS

	Page
ABSTRACT.....	iii
DEDICATION.....	iv
ACKNOWLEDGEMENTS.....	v
TABLE OF CONTENTS.....	vi
LIST OF FIGURES.....	viii
LIST OF TABLES.....	ix
 CHAPTER	
I INTRODUCTION.....	1
II LITERATURE REVIEW.....	3
2.1 Risk, Ambiguity and Welfare Measurement of Environmental Change.....	4
2.2 Incentive Compatibility and Valuation of Environmental Risks Reduction.....	6
2.3 Valuing Drinking Water Quality.....	12
2.4 Uncertainty and Risk in Environmental Context.....	14
2.5 Expressing Uncertainty in Contingent Valuation.....	17
2.6 Concluding Remarks.....	20
III STATISTICAL MODELS.....	22
3.1 Perceived Risk Model.....	22
3.2 The Random Utility Model with a Linear Utility Function...	23
IV SURVEY DESCRIPTION.....	26
4.1 Data Collection.....	26
4.2 Elicitation of Perceived Risk and Questionnaire.....	27
4.3 Descriptive Statistics.....	30

CHAPTER		Page
V	RESULTS.....	33
	5.1 Modeling Perceived Risk.....	33
	5.2 Calculating WTP with the Random Utility Model.....	36
VI	CONCLUSION.....	41
	REFERENCES.....	43
	APPENDIX A.....	49
	APPENDIX B.....	50
	APPENDIX C.....	52
	VITA.....	54

LIST OF FIGURES

FIGURE		Page
1	Comparison of adjusted and conventional estimate of WTP.....	18
2	Frequency distribution of confidence score.....	32
3	The risk ladder: personal risk of death per 100,000 over 20 years.....	49

LIST OF TABLES

TABLE		Page
1	Definition and summary statistics of respondent characteristics.....	31
2	Perceived risk models.....	36
3	The logit model estimation with binary discrete choice data.....	39
C1	Breusch-Pagan test.....	52
C2	Perceived risk models with heteroskedasticity-robust standard errors...	53

CHAPTER I

INTRODUCTION

The Environmental Protection Agency (EPA) recently approved a new regulatory standard for arsenic in public drinking water systems. In the past, 50 parts per billion (ppb) of arsenic in water or below was considered to be a safe level for human health. In 2001, the EPA has set 10 ppb as a new standard to protect the consumers served by the public drinking water systems from the chronic exposure of arsenic. Due to the Safe Drinking Water Act (SDWA), all the public drinking water systems have to comply with the new standard since 2006. The long term effect of over-intake of arsenic can cause cancers of bladder, lung, kidney, liver, skin and prostate (Tibbetts, 2005). Unfortunately, the relationship between dose and mortality/morbidity cannot be estimated accurately for concentration levels between 10 to 50 ppb (Nguyen et al., 2010). There remains uncertainty in the estimate of these risks, as smoking (the mixed effect of smoking and arsenic can increase lung cancer risk) and water consumption behaviors are heterogeneous, and many factors may confound the exact risk of exposure to a given amount of arsenic in drinking water.

Since the scientific estimate of risk is still in doubt, it's reasonable to assume that individuals prefer to determine water drinking and averting behavior based on their own risk perception rather than science-based estimate. Some papers have shown that this is a very common situation. On the other hand, numerous subjective risk studies implicitly

This thesis follows the format and style of *Journal of Agricultural Economics*.

assume the risk is precise and perceived without any uncertainty. On the contrary, in this manuscript I focus on the effects of subjective risk and its uncertainty on willingness to pay (WTP) for removing arsenic in drinking water. An empirical analysis is presented to show that subjective risk has a great influence on WTP. I also find that the residents living in arsenic hot spots are ambiguity averse, but the evidence is weak.

The remaining of this article is organized in the following manner. Chapter II reviews the literature of valuing environmental risk reduction. Chapter III presents a general perceived risk model and the random utility theory used to calculate WTP. Chapter IV briefly describes data collection and elicitation of subjective risk. Chapter V reports the empirical models and results. Chapter VI concludes the major findings and sheds light on future research.

CHAPTER II

LITERATURE REVIEW

In the last 30 years the leading theory of nonmarket valuation has been the contingent valuation method (CVM). CVM is a stated preference technique which allows the subjects of interest to explicitly reveal their preference over goods not traded in the conventional markets. For example, suppose you have to choose between the status quo and a proposed public program that improves air pollution in your community. After communicating the information of potential illnesses caused by polluted air, subjects may more clearly perceive mortality or morbidity risk based on their own conditions (age, smoking behavior, health status, exposure to polluted air, etc). Subsequently the subjects would be asked to respond “yes” or “no” to a WTP question and the aggregate WTP could be calculated as the welfare measurement of the proposed program.

Early studies assume that uncertainty is not involved with respect to WTP question and the perceived environmental risk, but a number of evidence has shown recently that potential upward bias might arise due to the ignorance of uncertainty and generally people do prefer less ambiguity. In this section I will present the literature most relating to risk and uncertainty as well as environmental valuation, and try to provide a framework to help us better understand why and how these literature might inform the arsenic problem in this paper.

2.1 Risk, Ambiguity and Welfare Measurement of Environmental Change

Risk and ambiguity have been the central topics in decision theory since the seminal work of Knight (1921) and Ellsberg (1961). Generally, risk implies the situation when the likelihoods of some events can be specified by a probability measure, and ambiguity represents the situation when the information is not sufficient for the individuals to assign probabilities to these risky events. Ellsberg's famous three-color urn example is well known as the "Ellsberg Paradox". This paradox indicates ambiguity aversion and is not consistent with subjective expected utility (SEU) model.

Many attempts to generalize the SEU model with ambiguity have been made in the last three decade. Some influential contributions should be noted here. Gilboa and Schmeidler (1989) proposed the maxmin expected utility (MEU) model with multiple priors to feature C-Independence and ambiguity aversion. Schmeidler (1989) derived the choquet expected utility (CEU) model which deals with nonadditive subjective probability and expected utility. However, the unclear definition of how and why a decision maker who is ambiguity averse uses the nonadditivity of probability to represent her preferences over events is one of the drawbacks of CEU model (Zhang 2002). Recently Klibanoff, Marinacci and Mukerji (KMM) (2005) described two thought experiments to develop a smooth ambiguity decision model. KMM claimed that their model was general and offered flexibility in modeling ambiguity, as well as achieved a separation between ambiguity and the attitude towards ambiguity. Epstein (2010) criticized KMM's theory by presenting the problematic nature of its foundation and the unclear behavior content

of the model. Other important papers include Segal (1987), Klibanoff (2001), Epstein and Schneider (2003) and Maccheroni et al. (2006), etc. Although a number of studies have applied these theories to model decision makers' preference over uncertain financial risk, only a few considered ambiguity in the context of environmental and health risks.

Mortality and environmental risks cannot always be assessed precisely when conflicting information from different sources comes to mind. To date, most welfare analysis of environmental risk reduction simply ignore uncertainty and model the risk exogenously. It's unrealistic to assume that individuals do not take uncertainty of a risky prospect into account when making a decision. Following KMM's theory, Treich (2010) developed a value of a statistical life (VSL) model to capture the attitude towards ambiguity, and found that VSL would be higher with ambiguity aversion than with ambiguity neutrality. The effect of ambiguity aversion on VSL is similar to an increase in the perceived baseline mortality risk. But Treich (2010) didn't obtain any empirical estimate to support his finding. On the other hand, individual heterogeneity, such as exposure level of toxic substance, smoking behavior, age and other factors, may well explain diverse subjective risk and ambiguity perceived by the people living in the same community. Riddel (2011) presented a decision-weighted random utility model based on Heckman and Willis' (1977) heterogeneous probit function. Her paper was about the nuclear-waste transport in Nevada, which was considered to cause environmental risk and threaten the health of local residents. Willingness to accept (WTA) was the key of welfare measurement. In her analysis, welfare losses were decomposed into perceived risk and the ambi-

guity surrounding risk. She found risk aversion and ambiguity aversion separately. Ambiguity aversion accounted for 12% increase of the external cost and led to a loss of social welfare. This novel model seems to be promising to inform WTP studies when ambiguous environmental risks are involved. Treich (2010) and Riddel (2011) cast some light on the alternative methods which are able to incorporate ambiguity into welfare measurement models.

2.2 Incentive Compatibility and Valuation of Environmental Risks Reduction

It's difficult to observe the value of environmental risks reduction in explicit markets. In a non-market economy, the lack of alternatives makes it necessary to apply CVM to measure the dollar-risk or risk-risk trade-off. Bockstael and McConnell (1999) may convince skeptics why CVM is so important when observed behavior fails to reveal gains and losses incurred by the subjects:

Individuals will change their behavior if they cannot adjust at the margin and if their next best alternative generates less utility than their current choice, even with environmental degradation. A localized water quality accident may not provoke a change in behavior if the next best alternative recreation site is still less desirable...the individual may, instead suffer in (behavioral) silence (p.26).

The past three decades have witnessed the substantial growth of studies in CVM. Due to the large number of studies in this field, the focus of the literature is on the valuation of risk reduction. Early works (Jones-Lee, 1974; Weinstein, Shepard and Pliskin,

1980) demonstrated that the maximum willingness-to-pay (WTP) for a risk change would increase with the level of risk. They implicitly assumed the value for a reduction in death risk from 0.8 to 0.7 is greater than the reduction from 0.2 to 0.1, which was consistent with expected utility and received little empirical testing to evaluate its consistency with individual behavior in the past. This finding was challenged by Smith and Desvousges (1987). They provided the first attempt to systematically collect variation in baseline risk and the corresponding value elicitation. Elicitation of the household value of risk reduction of exposure to hazardous waste was conducted in suburban Boston. In contrast to previous work, they asked the respondents to value risk reduction and varied the level of the baseline risks presented in the questionnaire across sample. They reported the marginal WTP across different baseline risks would increase with reduction in the baseline risk (one reason for this finding is the risk of exposure to hazardous waste was not fully understood, and the respondents might be uncertain about the risk change). Open-ended question which allows for a continuous estimate of WTP is believed to be difficult for subjects to understand as they are not familiar with this elicitation format. Although elicitation formats of WTP is not a priority in this paper, I still want to point out that Smith and Desvousges (1987) used the following valuation format in their survey:

In addition to \$___ per month, how much more in higher product prices and taxes would you be willing to pay each month to further reduce your risk of exposure to the company's hazardous wastes?

Economists prefer revealed preference and suspect stated preference techniques can shed light on welfare measure and nonmarket valuation (Diamond and Hausman, 1994). They think hypothetical questions and strategic behavior of subjects are major problems in CVM studies, and the corresponding WTP are highly suspicious. After the Exxon Valdez oil spill in 1989, a strong recommendation of the use of dichotomous choice (DC) format from National Oceanic and Atmospheric Administration (NOAA) panel, which was composed of some preeminent economists like Robert Solow and Kenneth Arrow, triggered numerous studies of environmental valuation with DC format. If a mechanism or institution can provide subjects with motives to truly and fully reveal their preferences, then it can be viewed as incentive compatible. DC format has been known to satisfy this condition for a long time. In mechanism design theory, Gibbard (1973) and Satterthwaite (1975) showed that a response format could not be incentive compatible unless it contained only 2 alternatives. The incentive compatibility of DC format in environmental valuation, however, was still in doubt due to the hypothetical context of CV surveys.

DC format was first introduced by Bishop and Heberlein (1979) in the field and was well accepted after mid 1980s. Some literature compared the difference between various hypothetical elicitation formats and real payments with a DC format to explore which hypothetical setting can provide a more reliable estimate of WTP. Cumming, Harrison and Rustrom (1995) (hereinafter CHR) found that responses generated by hypothetical DC format were significantly different from those elicited with real DC format. In CHR's experiments, subjects were simply asked if they would like to pay the stated

amount for the goods physically presented to them. Hypothetical subjects were found to respond much positively compared to real subjects. As a result the hypothesis that hypothetical DC format and real DC format could generate the same response was rejected. Since private goods such as electric juicer, chocolates and calculators were employed in CHR's experiments, some argued that incentive-compatibility of the DC format could still hold with the context of simple majority rule settings when only two social choices were involved. Cummings et al. (1997) designed a simple majority rule setting for a real public good to expose this claim in the experiment. The subjects were asked to respond yes/no to a proposed public program, and all had to pay if the majority agreed with it. The regression results showed that, holding other factors fixed, hypothetical payments had an increase of 19% in the chance that the subjects would say "yes" to the public program with statistical significance. Again the incentive compatibility of DC format in environmental valuation was rejected. Numerous experimental evidences suggest that hypothetical bias commonly exist in CVM studies (see Harrison and Rustrom 2008 for a literature review), and the environmental economists have more recently focused on how to mitigate hypothetical bias in the framing of CV questions.

Despite the fact that hypothetical bias could be a major problem, DC institution has still been the most widely used elicitation format in environmental valuation after 1990s. Poe and Bishop (1999) elicited the value of risk reduction with DC format and reported that the marginal WTP with various baseline risks was an inverse U curve using the cubic polynomial estimate. Interestingly, they used a close-ended format in their survey and had a conclusion similar to Smith and Desvousges (1987).

Individuals are always concerned about their health and willing to pay for avoiding health-related risks in the environment. Polluted air is apparently one of them: exposure from it can cause many respiratory-related illnesses. Health impacts of air pollution in developing countries are much larger than in United States (Carson, 2007). Alberini et al. (1997) elicited the value of health effects of air quality in Taiwan. Early morbidity studies were criticized for their abstract definition of symptoms. In this study respondents were asked to state their maximum WTP (a triple-bounded dichotomous choice format was used) to avoid a recurrence of a recent minor and acute respiratory-related illness. In order to make the symptoms less abstract, this large in-person survey documented the restrictions of normal activities, averting behaviors (changing the diet, frequency of visiting a doctor, over-the-counter medications) and duration of the illness in detail. The modeling framework explicitly took the potential endogeneity of averting behaviors into account, and considered the different values based on various types of air pollution illness. Including respondent social-demographic characteristics in the WTP function, they reported the elasticity (with respect to less illness) of WTP of 0.45, and found that respondents would like to state a higher WTP for a shorter duration of the illness. One drawback of this study is the WTP value estimated from self-described illness episodes may be unreliable if the respondents have difficulty in recalling their most recent episodes.

Although various risk elicitation formats can be applied to benefit-cost analysis, two problems remain in the field. First, in spite of the efforts made for a more comprehensible survey design in environmental valuation studies, it is still difficult for people

to understand and perceive small risk changes (Krupnick et al., 1999). Hammitt and Graham (1998) reported that 32% of the respondents didn't understand that 5/100,000 is smaller than 1/10,000 in a study of the value of mortality risks in United States. Even when interviewers tried to communicate the size of small risk changes in the survey, respondents could not distinguish the magnitude of these changes. In fact many studies (Jones-Lee, Hammerton and Philips, 1985; Smith and Desvousges, 1987) reported that the amounts of WTP showed no statistically significant difference with various risk reduction levels. This is the famous scope insensitivity problem.

Second, dollar/risk tradeoffs are difficult to make even when the respondents are fully aware of the difference of small risks they face. Typically respondents are not used to purchasing quantitative risk reductions in the markets (Krupnick et al., 1999). People always know that what risk factors may attribute to a given cause of death and would like to engage in risk averting behavior to reduce the risk. For example, people will state that they do more exercise like running or walking in order to avoid hypertension, heart attack or diabetes, while they don't know exactly how to quantify the benefits of this exercise.

Recognizing that people may not fully understand what is small risk change in the survey (e.g., Davies, Covello, and Allen, 1986; Fisher, Pavolva, and Covello, 1991; Rimer and Nevel, 1999), many studies have focused on risk communication in the context of CVM surveys.

2.3 Valuing Drinking Water Quality

Valuing drinking water quality is essential for the estimate of benefit of a public policy. A study of national water quality improvement from Carson and Mitchell (1993) is considered to be one of the most influential CV applications from a policy perspective. This research, which exhibited the first national estimate for a major public program based on a detailed CV scenario, has pioneered some methodological innovations. This study provided the WTP estimate as a function of water quality and demographic features which have been widely used in benefit-cost analysis.

Almost 50% of the U.S. population use groundwater as a source of drinking water. Nonpoint source pollution, which is typically caused by agricultural activities, is responsible for some water quality problems. Nitrate is a chemical substance which can cause gastric cancer in adults and blue baby disease in infants. Jordan and Elnagheeb (1993) asked the Georgia residents to rate their drinking water quality and apply CV to estimate WTP for reducing nitrate in drinking water. In this survey, the respondents were offered a series of values and asked to choose the highest one they are willing to pay in the payment card. The discrete choices were included in the econometric model for the estimate of WTP. They found no significant difference of WTP when respondents rated the drinking water quality differently. The aggregate WTP, from public water users and private well water users, was estimated as \$153.8 million per year.

Some drawbacks of this study should be mentioned: firstly, the respondents actually didn't know whether their drinking water was beyond the safe level of nitrate con-

centration, and they were just told in the survey that they have to suppose the concentration exceeds the safe level and required to circle the maximum WTP in the payment card. This question may exaggerate the aggregate WTP since the respondents with safe water were imposed to choose something unrealistic in life. Actually they should choose the WTP base on their real situation of drinking water. Secondly, reduction level of water was unknown. They told respondents: “To avoid the risk of increasing nitrate in my drinking water....., the permanent payment ABOVE my current monthly water bill is.....” The word “avoid” is ambiguous and didn’t provide any exact estimate of risk or nitrate reduction in drinking water. Thirdly, the answers of “very safe” to “don’t know” to the rating question WERE used to derive risk and uncertainty variables in the model, while it is not clear that how they could used one question to derive both variables. Fourthly, the rating question is not related to the estimate of WTP, but they expect to see respondents with a lower rating of drinking water quality would state a higher WTP. This did not make sense.

Most of the CV research in drinking water has focused on valuing changes in hypothetical (McClelland et al. 1992; Jordan and Elnagheeb 1993) probabilities of exceeding water quality standard or subjective perception (Hanley 1989; Silvander 1991). Poe and Bishop (1999) gave up both of them and valued the reduction of nitrate in drinking water with a known exposure level. Apparently the perceptions of risk are affected by the respondents’ real exposure level. They tested the concentration of nitrate in a laboratory for every respondent and asked them to value 25% reduction of it. Marginal WTP reached a peak at an intermediate level of nitrate. Note that respondents might not under-

stand how the reduction of nitrate could change the risk of mortality and morbidity they faced. Moreover, a fixed 25% reduction of nitrate suggests that this study is suspect to pass a scope test.

Trihalomethanes (THMs) is another harmful chemical substance in drinking water. Carson and Mitchell (1999) provided an example of how to communicate THMs risk in drinking water with respondents. They offered the respondents with a ladder describing basic risks (auto accidents, lightning, etc) everyone faces of dying, which become greater as people are older. Respondents could better understand the definition of small risk (THMs in drinking water) and know how to value it when it reduces to a certain level. Visual aid is necessary for its efficiency in risk communication, especially when small risk and its change are involved.

Adamowicz, Dupont, Krupnick and Zhang (2011) examined the value of THMs reduction in public water systems. This study provides a comparison between CVM and CE approaches and finds no systematic difference in WTP. CE approach allows for separate estimates of mortality and morbidity values in a consistent framework. They also separated the cancer risk and microbial risk in the survey and required the respondents to value their reductions respectively and found the cancer WTP is higher than the microbial WTP with longer cancer latency.

Valuations of chemical substances reduction in drinking water, such as nitrate, THMs, radon as well as PCBs, are similar. First, they can cause many diseases (the effects on the probability of mortality and morbidity are confounded) and the latency of diseases is long (this suggests a discount rate should be elicited). Second, most of them are small

risks, and it's difficult for individuals to understand the "small" concept and value their reductions properly. What is more, risk perception can be quite different based on various communication devices. Environmental and resource economists should be very careful about this and construct the validity of WTP estimate with an efficient risk communication device, which should be largely dependent on the context.

2.4 Uncertainty and Risk in Environmental Context

It's beneficial to further define "uncertainty" and "risk" here. These terms are used differently in a health context than is traditional in economics. By health risk, I mean the probability of mortality and morbidity with which an individual selected randomly from the population contracts an adverse health effect. The relationship between health risks and variables which generate them is not specified with certainty. As a result, the valuation of health risk is subject to error, and uncertainty should be used as a measure of the magnitude of this error (Lichtenberg, Zilberman and Bogen, 1989).

Taking uncertainty into account, in recent years environmental economists prefer to characterize a more complete picture of risk by using probability distribution to describe likelihood of different possible values of risks (Fischhoff and Furby, 1988; Poe and Bishop, 1999; Cameron, 2005a; Johnson et al., 2008;).

Rai and Krewski (1998) presented a general framework for the estimate of uncertainty in risk assessment. They got the results based on a multiplicative model for cancer risk from ingestion of radon in drinking water, where the risk R was the product of n risk

factors. These risk factors were assumed to follow a distribution with one or more parameters, which also characterized the distribution of uncertainty, to reflect the variability in the population of interest. They concluded that collecting more information of more influential risk factors can help reduce total uncertainty in risk.

Nguyen, Jakus, Riddel and Shaw (2010) developed a formal model to estimate people's perceived health risk related to arsenic in drinking water. As it was mentioned before, people always have difficulty in interpreting small risk and its change, as well as many variables such as smoking, averting behaviors and latency can confound perceived risk of individuals even they are drinking the water with same concentration level of arsenic. By using a risk ladder as a risk communication device in the survey, respondents obtained scientific information about the risk of arsenic in drinking water, and they were also told the exposure levels of arsenic in their communities. They modeled the risk as a random variable with its probability distribution whose variance reflects uncertainty of risk. They found that both scientific information and uncertainty related to individual's own condition play important roles in the estimate of perceived risk.

In this case, the key was to figure out the probability of perceived risk, and therefore uncertainty could be treated as the variance of it. On the contrary, a lot of literature deals with this problem in a more explicit way: the certainty questions are presented directly to the respondents. But most of these studies elicit certainty attitude towards the bid, not towards the risk. In my thesis, I will apply an explicit approach to calibrate uncertainty of perceived risk. To my knowledge, it's necessary to introduce the explicit methods which incorporate uncertainty questions in environmental valuation.

2.5 Expressing Uncertainty in Contingent Valuation

As I mentioned before, the NOAA Panel sanctioned the use of dichotomous-choice questions in CV study which frames the contingent market as a referendum, and the panel also recommended the “don’t know” or “no answer” response option in addition to the customary “vote for/vote against” options (Arrow et al., 1993). Yet there is no clear guideline which interprets the application of this “don’t know” response. Incorporating uncertainty in CV is a practice of this recommendation.

Traditional wisdom assumes that people are certain about their preferences. Actually people’s lives are full of uncertainty in the future, which suggests that preferences may be uncertain over time if there is a great difference between current and future states. To characterize the degree of preference uncertainty, Li and Mattson (1995) elicited the confidence level of each “Yes/No” response to the discrete choice question in the forest environment valuation study. After presenting a single-bounded, closed-ended valuation question, they asked “How certain were you of your answers to the previous question?” Respondents were required to reply to this confidence question with a scale from 1% (absolutely uncertain) to 100% (absolute certain). The uncertainty adjusted estimate of WTP (Swedish Kronor) shows that the conventional estimate of WTP might be upward-biased (Figure 1). Ready et al. (1995) had a similar conclusion based on qualitative responses of uncertainty in the follow-up questions.

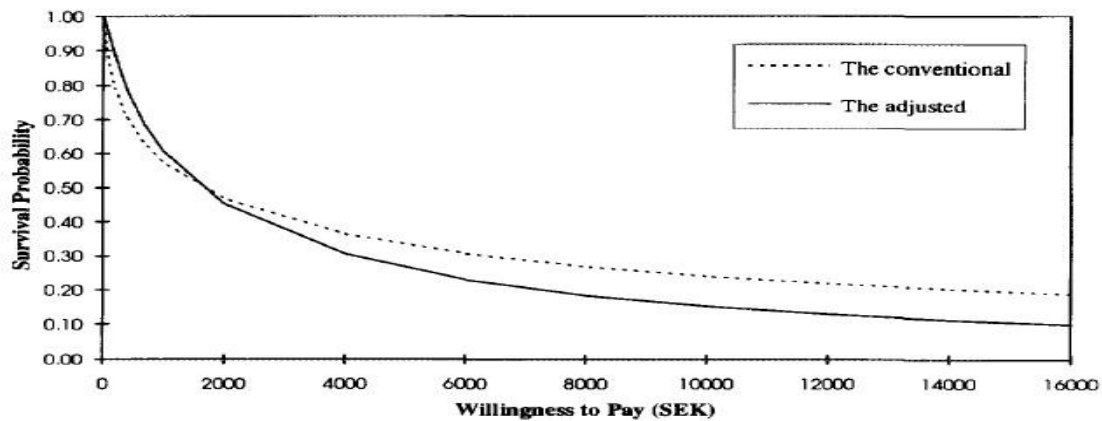


Figure 1 Comparison of adjusted and conventional estimate of WTP

(Resource: Li and Mattson (1995))

Follow-up certainty questions (FCQ) are not uncommon in CV studies. Champ et al. (1997) required respondents with a “Yes” dichotomous choice to state how certain they were with their maximum willingness-to pay for the public program, on a scale from 1-10 (“very uncertain” to “very certain”). They separated the estimate of WTP functions for each certainty level. Welsh and Poe (1998) adopt a two-dimensional decision matrix with multiple-bounded discrete choice (MBDC) approach: one dimension indicates respondents’ WTP for implementation of the policy, and the other dimension allows the respondents to specify their voting certainty of WTP through “definitely yes”, “probably yes”, “not sure”, “probably no” and “definitely no” options. Welsh and Poe used a multiple-bounded logit model to estimate WTP functions for each certainty level. Vossler, Ethier, Poe and Welsh (2003) compared WTP distributions based on FCQ and MBDC models and suggested theoretical and empirical trade-offs should be made between both approaches, since there was no clear preference between methods on theoret-

ical grounds. They found the FCQ responses correspond with relatively low levels of certainty in the payment. FCQ can be regarded as an *ex post* adjustment and MBDC as an *ex ante* adjustment. The effects of both adjustments on certainty level remain an empirical question. Apparently more comparative analysis is needed.

Alberini, Boyle and Welsh (2003) employed a random effects probit model and an extension of Wang's (1997) random-valuation model, both of which retained the categorical response characterized as "Yes" or "No" decisions, to estimate WTP from a MBDC dataset. Previous models of MBDC assumed implicitly that respondents with a MBDC elicitation format should have a fixed underlying distribution of WTP, which was challenged by Alberini et al. as they obtained separate and uncorrelated WTP distributions in their result. Vossler and Poe (2005) replied this finding with replication of the same dataset and another two MBDC datasets with probit and random-valuation models. They were unable to replicate the same uncorrelated result in the probit model, and reported that there was a single and highly correlated underlying WTP distribution in each datasets. Apparently, the underlying WTP distribution of MBDC is still an open question in the field.

In a recent study, Champ, Alberini and Correias (2005) developed another elicitation format for respondents to express uncertainty of stated WTP for the Noxious weeds Control Program. In the treatment group, respondents had three options: the standard dichotomous-choice response (vote in favor/vote against) plus an unsure response option. In the control group, no unsure response option is provided. They found there were more unsure respondents with a higher offer amounts and respondents with lower income

were more likely to provide an unsure response in the survey. In the treatment group less “vote for” responses were documented (62% versus 76% in control group) and almost 25% of the respondents choose “unsure” option to express their uncertainty. The reasons provided by respondents why they choose unsure option are various: uncertainty about future income, benefits of the program, demand for more information about the program, etc. They concluded that unsure response is distinct from the vote in favor and vote against responses, which implies a legitimate explanation for unsure response.

Allowing for the expression of uncertainty in CV study is necessary, since respondents are always uncertain about various aspects of a public policy and their preferences in the future. Unsure response option can help adjust and provide a more reliable WTP estimate function. But surely the debate over the format of presenting the unsure response to respondents will go on and more comparative studies are expected in the future.

2.6 Concluding Remarks

A few papers conduct risk analysis of arsenic in drinking water. Shaw et al. (2006) incorporated perceived mortality risk from arsenic into models of drinking behavior and valued the reduction of the risk in four arsenic hot spots. Konishi et al. (2010) investigated the effect of new arsenic standard of tap water on economic benefit. Konishi and Adachi (2010) took into account both imperfect information and the dependence of welfare value on the self-protection choice, and proposed a general empirical strategy to es-

timate WTP to avoid exogenous environmental risks. In addition to welfare analysis, they also estimated policy which informs and educates public about the arsenic risk simultaneously with public risk mitigation.

As I have mentioned before, some CVM papers have explored how certain the subjects were about their stated WTP or the hypothetical environmental program. While none of these previous works tried to figure out how the subjects' confidence with the perceived risk per se can be related to their stated WTP. As most CVM studies simply ignore ambiguity and treat the risk as unambiguous, it's critical to incorporate ambiguity into the WTP model when precise risk is absent.

CHAPTER III

STATISTICAL MODELS

3.1 Perceived Risk Model

I model the perceived risk with the regression

$$y = \mathbf{X}\mathbf{\beta} + u \quad (3.1)$$

where \mathbf{X} is a $1 \times K$ vector of explanatory variables, $\mathbf{\beta}$ is a $K \times 1$ vector of coefficients to be estimated, y is perceived risk reported by the subjects (which is the probability of dying from arsenic mortality risk), and u is the error term (which can consist of omitted variables and measurement error). K is dependent on the number of explanatory variables we include, and u is scalar while y is not if the subjects provided a range of perceived risk. This regression model is proposed to see how confidence score and other factors may influence respondents' perceived risk. In particular we're interested in the role of confidence score, so it will be included in a full model and the comparison between this full model and the parsimonious model is available. Confidence score can be viewed as the degree of ambiguity associated with perceived risk, and it's important to learn the relationship between perceived risk and its ambiguity, since by far there are few literatures linking them together in the context of health and environmental safety.

3.2 The Random Utility Model with a Linear Utility Function

Hanemann's random utility model (1984) is often used as the typical parametric model with which we will apply to estimate WTP. Here I use Haab and McConnell's (2003) comprehensive review to present the model. The random indirect utility function is generally specified with a deterministic part of the preference function that is linear in income and other explanatory variables

$$u_i = u_i(y, z, \varepsilon_i) = v_i(y, z) + \varepsilon_i \quad (3.2)$$

where $i = 0$ indicates the status quo and $i = 1$ indicates a change of environmental quality. Income is expressed by y and z is the vector of attribute related to the respondent. The probability $Pr(yes|t)$ of the respondent saying "yes" to a bid t for a change in environmental quality is defined as

$$Pr(yes|t) = Pr(v_1(y - t, z) + \varepsilon_1 > v_0(y, z) + \varepsilon_0) = Pr(-\Delta v < \varepsilon) = 1 - G_\varepsilon(-\Delta v) \quad (3.3)$$

where $\Delta v \equiv v_1(y - t, z) - v_0(y, z)$, $\varepsilon \equiv \varepsilon_1 - \varepsilon_0$. The cumulative distribution function of the error term ε is given by G_ε . $S(t)$ indicates the WTP survival function $Pr(WTP \geq t)$, and we suppose that WTP is distributed in the range of 0 to B. Formally the mean WTP is estimated by $E(WTP) = \int S(t)dt$. Since $Pr(yes|t) = Pr(WTP \geq t) = S(t)$, we can further prove that

$$E(WTP) = \int Pr(yes|t) dt = \int (1 - G_{\varepsilon}(-\Delta v)) dt \quad (3.4)$$

We specify the parameters linearly and $\Delta v \equiv \mathbf{x}\beta$, where \mathbf{x} contains y , z and t and β is the vector of coefficients to be estimated. We should employ the maximum likelihood method, when ε_i is specified by a certain distribution to calculate $Pr(yes|t)$. Typical binary response models such as the logit model may be used if we specify ε_i by an extreme value distribution.

Generally we can simply estimate WTP if the coefficients are known from the binary response models. In this study we are interested to know how the perceived risk, which is different between status quo and the proposed CV scenario, may influence WTP. If the respondent says “yes” to a bid, then WTP indicates that he or she is at least indifferent in the context of random utility. Intuitively the subject should not be worse off if he or she agrees to pay the bid. Let’s redefine WTP in the following form

$$\alpha_1 z + \beta(y - WTP) = \alpha_0 z + \beta y \quad (3.5)$$

“yes” to a bid “no” to a bid

where $\alpha \equiv \alpha_1 - \alpha_0$, β is the marginal utility of income that is assumed to be identical between the two CV states. Simple algebra yields

$$E(WTP | \alpha, z, \beta) = \alpha z / \beta \quad (3.6)$$

I can estimate the mean WTP from (3.6). The linear model discussed above leads to a simple application of econometrics to dichotomous choice CV studies. Note that the confidence score of perceived risk is one of the explanatory variables in z , and I will present how this attribute may inform the WTP in Chapter V shortly.

CHAPTER IV

SURVEY DESCRIPTION

4.1 Data Collection

The data has been used by Jakus et al. (2009) and Nguyen et al. (2010). In late 2006, interviewers randomly contacted the sample of subjects living in the arsenic hotspots of the United States, including Albuquerque, New Mexico; Fernley, Nevada; Oklahoma City, Oklahoma; Outagamie County/Appleton, Wisconsin. Water used by the residents of the first three locations comes from public water supply systems, which were not in compliance with the new federal standard of 10 ppb for arsenic. Outagamie County/Appleton of Wisconsin was of interest in our study as high arsenic concentration of privately owned wells in this area exceeded the new standard and was not regulated under Safe Drinking Water Act. Note also that the random sample of subjects was not the representative of the population living in United States, since the drinking and risk averting behaviors of the people facing the risk of arsenic contamination in their water systems was of major interest.

A telephone-mail-telephone survey format was applied in the communication of arsenic related information and the scientific estimate of cancer risks associated with drinking water contaminated by arsenic. The first stage is screener survey: interviewers contacted the subjects through random-digit dialing, and obtained the demographic information and learned whether they would like to receive an information booklet and be

participants in the follow-up survey. Interviewers could also detect the subjects who didn't pay their water bills, like renters, and excluded them simultaneously. The subjects who consented to participate in the follow-up survey would receive brochures with information on arsenic risks in the mail and the new telephone surveys were scheduled immediately.

The key information reported by the brochure was the arsenic concentration in local areas and the cancer risks of ingesting arsenic in water with regard to the new EPA standard. For the subjects served by public systems, the mean exposure level of arsenic was determined, as was required by the EPA, and the ranges of arsenic concentration were provided to the subjects served by private systems. We allowed the subjects to have at least one week to read the brochure prior to the elicitation of perceived risk during the final follow-up survey.

4.2 Elicitation of Perceived Risk and Questionnaire

Studies on risk analysis generally characterize health risks in the form of probabilities. In this research, the best scientific estimate of the "background" level of lung and bladder cancer is 60 deaths per 100,000 people, but if an individual is exposed to arsenic in drinking water at a concentration of 50 ppb for twenty years, the mortality rate will rise to 1 death per 100 people. All other things being equal, smoking behavior doubles the risk to 2 deaths per 100 (US Environmental Protection Agency, 2000). Then we converted these risks to probabilities, and the econometric models can be applied to the

analysis of how perceived risks may influence one's decision on willingness to pay for a public program of arsenic removal. We stress on perceived risk for a particularly important reason: individuals make decisions based on their own perception rather than scientific estimates.

Communicating risk information effectively is not an easy task, specifically when the probabilities are small. As we have mentioned in Section 2, it is common to see that respondents always have difficulty in understanding the small changes of health risk in CV studies (Hammitt and Graham 1999). A handful of literature reported that graphical/visual communication devices are helpful in comprehension of risk. In order to determine which communication tool can better assist in comprehending small risk changes, focus groups in Nevada, Utah, and Wisconsin were recruited and exposed to various text and visual formats for arsenic risk communication. We found the respondents of focus group strongly preferred risk ladder to the risk grid. Risk ladders have been widely used as a risk communication tools in environmental valuation in the past decade (Corso, Hammitt and Graham, 2001; Carson and Mitchell, 2006). Although it is not a panacea for solving all the risk communication problems, the risk ladder has fewer limitations compared to other alternatives. This pre-survey test led us to decide to use risk ladders as the mortality risks presented to the focus group in this form were best understood.

Perceived risk was elicited in this way: respondents were asked to consider the risk they faced based on the reported arsenic concentration in their communities and the amount of water they drink, and place a mark which best captured their perceived risk on

the risk ladder, if they were very certain about the risk they perceived. Some recent studies show that both perceived risk and uncertainty about the perceived risk may affect behavior and willingness-to-pay decision making (Cameron, 2005b; Riddel and Shaw, 2006). Previous research assumes that respondents can provide exact point estimates of perceived risk, and the uncertainty about it is always ignored. But this kind of uncertainty does exist in the context of non-market valuation if environmental risk is involved; therefore we designed a new setting to allow the respondents to reflect their uncertainty about the perceived risk: respondents may place two marks on the risk ladder to specify the lower and upper bounds of the perceived risk, if they're uncertain about it. After the risk elicitation section, the respondents were also asked to state their confidence level of the perceived risk explicitly (see Appendix A and B1 for risk ladder and questions).

In CVM study, welfare measurement depends largely on whether the hypothetical market is able to convince the respondents to state their true preference over risk-money tradeoffs. Willingness to pay (WTP) was elicited by using a single-bounded dichotomous choice format. In the follow-up survey, a hypothetical risk reduction market was created and each respondent was told that in the next five years water supplier would keep collecting an amount of X dollars per month, per household to treat the water in order to meet the new federal drinking water standard for arsenic. The respondents need not to specify an exact amount they were willing to pay, and we are interested in their responses of “Yes” or “No” to the randomly selected “price” presented to them (see Appendix B2 for the WTP question). Interviewers reminded the respondents of their own risks of dying from drinking the tap water routinely with their current arsenic concentra-

tions, as well as keeping their monthly budget in mind to answer the WTP question. Note also that interviewers didn't imply an exact risk reduction level, like 25%, 50%, or 75%; instead they used the term "safe" to describe the tap water with the arsenic removal treatment. In another word, it is implicitly assumed that the risk reduction level is 100%, and no mortality risk relating to arsenic is involved after the treatment is conducted.

4.3 Descriptive Statistics

Table 1 shows the simple descriptive and summary statistics of respondent characteristics associated with demographics, smoking behavior and water quality. The average age of respondents was 48, and they had generally lived in their current residence for 11.25 years. Some 57.73% of respondents were male, and the average monthly increment to water bill, which was randomly presented to the respondents, was \$8.71. The confidence score of perceived risk is on a scale of 1% to 100%, with 1% being very uncertain and 100% being totally certain. It's interesting to see if the magnitude of subject's uncertainty can be quantified using stated preference technique. The mean confidence score was 45.86%, suggesting that the respondents had some degree of uncertainty about the perceived risk. See Figure 2 for the frequency distribution of confidence score. About 91% of the respondents reported their health status as "good" or above, and the remaining 9% assessed themselves as having a "fair" or "poor" health status. Almost 13% of the respondents were current smokers, with 53% claiming that they had never smoked and one third stating that they had already quit smoking. A little more than two thirds of respon-

dents received tap water from a public system; the remaining respondents received it from a private well. The health concern about arsenic in tap water, which was elicited using a discrete scale from 1 (not at all concerned) to 5 (very concerned), implied the concern attitude was quite diverse among respondents.

Table 1. Definition and Summary Statistics of Respondent Characteristics

Variable	Mean/Proportion (standard error)
Age in years,	48.32 (0.84)
Years in current residence,	11.25 (0.67)
Gender, (% male)	57.73% ^a
Bid: monthly increment to water bill, (Bids of \$3.50, \$7.00, \$10.00 and \$13.00 are randomly offered to the respondents)	\$8.71 (0.18)
Confidence score of perceived risk, n=289	45.86 (1.76)
Self-rated health status,	
Mean	2.18 (0.05)
Excellent (1)	27.11%
Very good (2)	37.61%
Good (3)	26.53%
Fair (2)	7.58%
Poor (5)	1.17%
Smoking	
Current smoker,	12.83%
Never smoked,	53.35%
Quit smoking	33.82%
Water system and water quality	
Tap water from a public system,	68.51%
Health concern about water quality relating to arsenic,	
Mean	3.19 (0.08)
Not at all concerned (1)	20.41%
(2)	13.12%
(3)	21.28%
(4)	11.66%
Very concerned (5)	27.70%
Perceived risk	
Point estimate, n=190	0.0057 (0.00075)
Upper bound of the range, n=99	0.0072 (0.00092)
Lower bound of the range, n=99	0.0017 (0.00034)

Note: The full sample size n=353, if not otherwise indicated.

^aStandard error is not provided for proportion data.

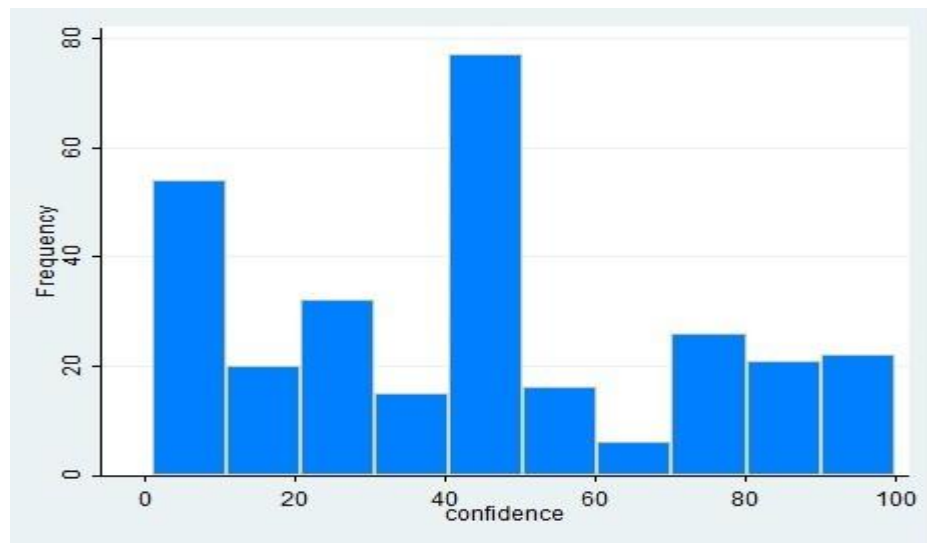


Figure 2 Frequency distribution of confidence score

CHAPTER V

RESULTS

It's reasonable to assume that risky decision under uncertainty is largely dependent on subjective perception of risk. Therefore my models are developed with three goals in mind: first, I would like to know whether the perceived risk can be explained by the household characteristics. The factors that may greatly influence the perceived risk are of my interest. Second, I would like to link the predicted perceived risk to the estimate of mean WTP. To what extent did the respondents consider perceived risk for the economic value of mortality risk reduction relating to arsenic in tap water? Third, the stated confidence score of perceived risk might be informative in both perceived risk models and WTP measure models.

5.1 Modeling Perceived Risk

Following Jakus *et al.* (2009) and Shaw *et al.* (2010), I estimate the perceived risk models in a similar way. For the respondents who provided a point estimate of perceived risk, a simple ordinary least square (OLS) model is used. For the respondents who were uncertain about their perceived risk and provided a range, I apply a separate interval regression model. Prediction of the perceived risk could be obtained in both models, and I explore whether it influences the probability of “yes” response to a bid in the logit model and the WTP estimate. There are many potential model specifications, in large part due

to the numerous demographic variables (some of which are not reported in Table 1) collected in the survey. I present a relatively parsimonious specification based on the goodness of fit and significance of explanatory variables. I focus on the coefficients which are significant different from zero at 0.1 level, as well as some variables of interest.

Table 2 presents the regression-parameter estimates for perceived risk. Let's turn to the OLS models first to see how the respondents who provided a point estimate perceived the arsenic mortality risk. *Arsenic Concentration*, which was reported by the local water authority or known by the private wells users, is used instead of PPB since the exact PPB levels to each household were not available. As the *Arsenic Concentration* goes up, perceived risk also increases. The respondents served by the public water system perceived more risk than those who were served by private wells. Better *Health Status* suggests less risk perceived by the respondents, perhaps resulting from the fact that people with good health status are less sensitive to the environmental risk. *Current Smokers* show that they also perceived more risk than those who have never smoked, which might be attributed to the risk ladder that effectively communicated the risk information with respondents. Both OLS models have very similar estimates, and the only notable difference between them is the second one contains *Confidence Score* of perceived risk. Though the positive coefficient means uncertainty implies less perceived risk, it's not statistically significant at conventional levels (p-value is 0.41). It's possible that the subjects were not familiar with this uncertainty elicitation mechanism, thus they just provide some mindless estimates of *Confidence Score*. This may explain why it doesn't play a significant role in the perceived risk models.

The interval models reports quite different estimates. Shaw *et al.* (2010) speculates that this might be due to the group of respondents who felt very uncertain about their arsenic mortality risks, and the underlying preferences between “certain” respondents and “uncertain” respondents could be quite different. Surprisingly the coefficients of *Arsenic Concentration* are negative, but the p-values are rather high, which implies the corresponding coefficients have no significant influence on perceived risk. Unlike the estimates from OLS models, males thought they perceived more risks than females. Living years in current residence is positively related to the risks. Again, the coefficient of *Confidence Score* is positive and not significant (p-value is 0.62).

I speculate that *Confidence Score* might shed light on the heteroskedasticity problem in both OLS and interval models, since it’s possible that the degree of uncertainty is correlated with the omitted variables which capture the heterogeneity not included in the model. Breusch-Pagan is widely used by regressing the squared error term on the covariates to check which factors may be correlated with heteroskedasticity, and my Breusch-Pagan test shows that actually not *Confidence Score* but other variables account more for the heteroskedasticity (see Table C1 in Appendix C). In recognition of the heteroskedasticity in my perceived risk models, I try to justify the use of OLS models and interval models using heteroskedasticity-robust standard errors, with which I can gain more efficiency for the estimators. Comparing the full models in Table 2 and the models in Table C2, I find the effect of heteroskedasticity on efficiency is trivial (see Table C2 in Appendix C). As a result, the perceived risk models are still valid and reliable in terms of this.

Table 2. Perceived Risk Models

Variable	Parsimonious models (without confidence score)		Full models (with confidence score)	
	OLS Model 1	Interval Model 1	OLS Model 2	Interval Model 2
Constant	-0.00988 (0.058)*	0.00035 (0.90)	-0.011 (0.041)**	0.00017 (0.95)
Arsenic Concentration	0.00016 (0.051)*	-0.00002 (0.71)	0.00016 (0.054)*	-0.00002 (0.68)
Public Water System	0.0074 (0.002)***	0.0013 (0.35)	0.0076 (0.002)***	0.0013 (0.37)
Male	-0.00097 (0.49)	0.002 (0.003)***	-0.00099 (0.48)	0.002 (0.004)***
Year in Current Residence	-0.000083 (0.16)	0.0001 (0.001)***	-0.000077 (0.19)	0.0001 (0.001)***
Health Status	0.0027 (0.01)**	0.00009 (0.83)	0.0028 (0.01)**	0.00009 (0.84)
Never Smokers	-0.002 (0.20)	-0.0001 (0.92)	-0.002 (0.22)	-0.00005 (0.96)
Current Smokers	0.007 (0.002)***	0.0018 (0.16)	0.007 (0.003)***	0.0019 (0.16)
Confidence Score of Perceived Risk			0.00002 (0.41)	0.000007 (0.62)
N	190	99	190	99
Adjusted R ²	0.216		0.215	
Chi-Square		22.52		22.77

Notes: P-values in parentheses. *, **, *** indicate p-values < 0.1, 0.05, and 0.01.

5.2 Calculating WTP with the Random Utility Model

My next task is to estimate the WTP using the *Perceived Risk* predicted and pooled from previous models. The path-breaking paper of Hanemann (1984) is the modeling framework applied to my dichotomous choice data. First I have to employ a binary response model (e.g., logit or probit) to estimate the effects of explanatory variables on the probability of accepting the discrete bids randomly assigned to respondents. Depending on the chosen variables, the estimated parameters are used to calculate monthly WTP which is

a function of the random component assumed for preferences. Generally speaking, WTP is the measure of welfare change making the individual indifferent between the status quo and the proposed public program or CV scenario.

Intuitively, *Confidence Score* is treated as the degree of ambiguity and uncertainty, then I could simultaneously take risk and its ambiguity into account to model decision making: to agree or not to agree with the proposed public program. I would also like to see if the WTP from the latter two are different from the first one. I present three different logit models in Table 3: the first one is parsimonious and the basic for comparison. Perceived risk values in the second logit model are slightly different from the first one: it includes updated information of confidence score. I directly incorporate *Confidence Score* in the third logit model and *Perceived Risk* remains unchanged (without updated information of *Confidence Score* at the first stage).

In my logit model, the dependent variable is defined as 1 if the respondent said “yes” to the bid and 0 otherwise. See Table 3 for the results. *Bid*, which was randomly presented to the respondents, has a negative influence on the probability of a “yes”. This is consistent with what I expect: as the bid goes up, the respondents are more likely to decline it. Adding an interaction term between the *Bid* and the *Perceived Risk* makes the *Perceived Risk* significantly (and positively) related to the probability of a “yes”. It’s reasonable that the higher risk the respondents perceive, the more likely they are willing to pay for its reduction. *Current Smokers* has a significant negative sign in both models, and this suggests that those who smoked might be risk takers and they cared less about their health, even they were able to perceived more risk from arsenic exposure (see the

results of perceived risk models in Table 2). *Never Smokers* has a negative sign, and it implies that the respondents who never smoked were less likely to accept the bid, which might be due to the fact that they have less perceived risk from arsenic exposure. *Health Concern* shows that the respondents who were concerned about their health from the negative effect of arsenic were more willing to say yes to the bids, and the signs are significant in both models.

Respondents served by public water systems seemed to be less likely to vote for the hypothetical arsenic removal program, which is opposite to what I found in perceived risk models (these respondents thought they have relatively higher risk compared to private well users), but the coefficients are not significant in both models (p-values are 0.37 and 0.55, respectively). Note that although the updated *Perceived Risk* and *Confidence Score* weakens the significance of some coefficients in the latter two models respectively, the log-likelihood of these two logit models are actually greater than the first one ($-169.12 < -157.16 < -145.30$). Calculation of WTP is based on the coefficients I get from the logit models, and I are extremely interested to see if the updated logit models make the WTP significantly different from that estimated from the basic logit model. The confidence intervals of WTP presented in Table 3 implies that updated WTP are both significantly greater than the first WTP, with almost 95% confidence.

Ambiguity aversion indicates an attitude of preference for “certain” risk over “uncertain” risk, and its difference from risk aversion should be specified: it’s a rejection of types of risks based in part on measure of their uncertainty, not simply on their magnitude. First I focus on the parsimonious model, which contains no information of

Table 3. The Logit Model Estimation with Binary Discrete Choice Data

Variable	Logit Model 1 (Parsimonious model)	Logit Model 2 (with updated perceived risk)	Logit Model 3 (with confidence score)
Constant	1.91 (0.052)*	0.86 (0.32)	1.21 (0.20)
Bid	-0.10 (0.125)	-0.066 (0.316)	-0.08 (0.27)
Perceived Risk	204.06 (0.10)*	233.60 (0.052)*	183.36 (0.14)
Age	-0.012 (0.19)	-0.003 (0.60)	-0.003 (0.60)
Current Smokers	-1.0 (0.035)**	-0.87 (0.081)*	-0.88 (0.083)*
Never Smokers	-0.52 (0.096)*	-0.12 (0.70)	-0.28 (0.40)
Health Concern	0.22 (0.017)**	0.20 (0.035)**	0.20 (0.054)*
Public	-0.28 (0.37)	-0.19 (0.55)	-0.25 (0.46)
Perceived Risk×Bid	19.73 (0.11)	22.01 (0.061)*	19.34 (0.12)
Confidence Score of Perceived Risk			0.0026 (0.59)
N	291	291	249
Log-likelihood	-169.12	-157.16	-145.30
Mean WTP	\$12.46	\$14.96	\$13.64
95% Confidence Interval of Mean WTP	[\$11.83, \$13.10]	[\$13.09, \$16.83]	[\$13.21, 14.07]

Notes: P-values in parentheses. *, **, *** indicate p-values < 0.1, 0.05, and 0.01. 39 missing perceived risk values were predicted using OLS regressions and interval regressions in table 2.

confidence score. The mechanism of “point” and “range” estimates of perceived risk is helpful to reveal the certainty of subjects qualitatively. It’s interesting to see if “certain” subjects who provided a point and “uncertain” subjects who provided a range had different WTP. The mean of “certain” WTP and “uncertain” WTP are \$12.73 and \$12.06, respectively. But I fail to reject the null hypothesis that they are indifferent with statistical significance, thus there is no clear evidence of ambiguity aversion in terms of this. Am-

biguity aversion can also be revealed in a very simple way: if the respondents had less uncertainty over perceived risk, they were more likely to treat it and pay a higher cost to remove arsenic in drinking water. More *Confidence Score* implies less ambiguity or uncertainty over perceived risk. Recall that the signs of *Confidence Score* in the perceived risk models and the third logit model, and the sign of *Perceived Risk* in the logit models are all positive, so I may conclude that in the latter two logit models, the marginal WTP (MWTP) with respect to *Confidence Score* are positive, based on calculation from equation (3.6) where *Perceived Risk* and *Confidence Score* are both in the numerator. I can assert respondents are ambiguity averse¹, though this assertion might be weak due to the insignificance of *Confidence Score* in the models.

¹Shaw and Riddell (2009) find ambiguity affinity rather than ambiguity aversion with the same dataset using a modal random utility model.

CHAPTER VI

CONCLUSION

Individuals are always involved with contaminant risks in drinking water without precision. Previous risk-related literature in environmental economics rarely discusses uncertainty about the mortality risks. Instead, simple point estimate of the risk is often used assuming that uncertainty does not exist. In contrast with previous research, I introduce the confidence score of perceived risk to allow for having some degree of uncertainty in the models. One notable finding in my study is smokers could perceive more mortality risk from exposure to arsenic, but they were less interested in the proposed CV scenario. Therefore I infer the smokers are kind of risk takers when they have to make risky decision associated with health. My empirical models also show that the respondents in arsenic hot spots have a higher WTP if the degree of ambiguity reduces. As a result I reports weak evidence of ambiguity aversion. One drawback of this paper is I treat the stated ambiguity (confidence score of perceived risk) with a relatively simple approach. Future research could link the stated ambiguity to the method proposed by Nguyen *et al.* (2010), where the risk is viewed as a random variable with an estimable probability distribution whose variance reflects uncertainty, which calls for a more computationally complicated model.

Finally I would suggest that risk ladder, the small risk communication tool used in my survey, has played an important role. The perceived risk models show that smokers understood they were exposed to a higher risk than nonsmokers, as well as the respon-

dents knew that higher arsenic concentration was positively related to higher risks. Policymakers or scientists might consider addressing the risk communication problem in a similar way, especially when the uncertainty about mortality risk is involved.

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APPENDIX A

VISUAL AID FOR RISK COMMUNICATION

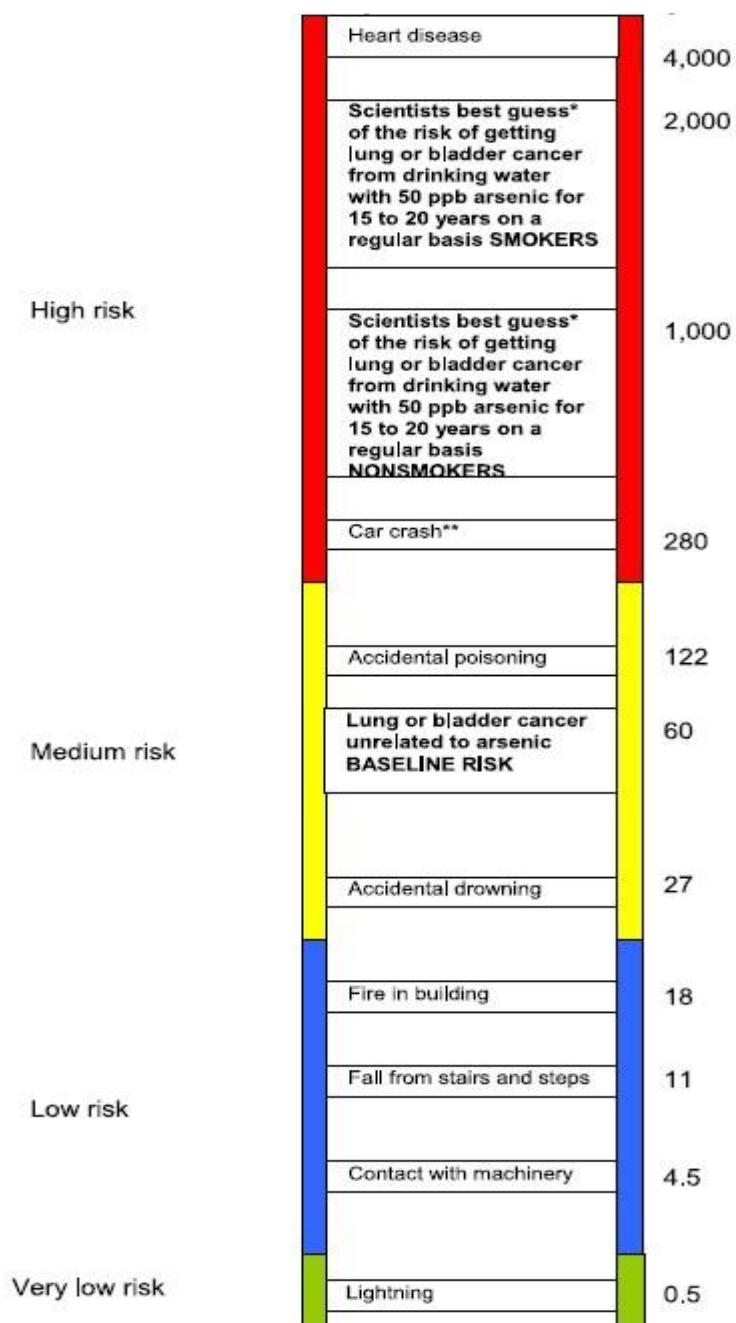


Figure 3 The risk ladder: personal risk of death per 100,000 over 20 years

APPENDIX B
IMPORTANT QUESTIONS FROM FOLLOW-UP SURVEY

B1. Perceived Risk

I want to ask you about the risks that you think you face. Look at Page 9 of the brochure,

Risk Ladder 1. Did you make one mark or two marks?

- 1 One mark
- 2 Two marks
- 3 Cannot decide where to mark
- 4 Did not mark any yet
- 5 Why do you refuse to make the marks?

If certain: What line did you make your mark on?

_____Line number

If uncertain: What was the highest line you made your mark on?

_____Line number

If uncertain: What was the loIst line you made your mark on?

_____Line number

The brochure provided you with information that allowed you to estimate your risk of dying from lung or bladder cancer. You might be confident in this estimate, or you might not be confident. On a scale of 1 to 100, with 1 being very uncertain about your risk and 100 being totally certain, how certain are you about the risks that you face?

_____ % of confidence (1-100%)

B2. Willingness to Pay

What is your response for Q1? (Would you be willing to pay an increase in water rate of \$ [WTPBID] per month to obtain safe tap water from your public supplier? Please keep your monthly budget in mind as you answer.)

- 1 Yes
- 2 No
- 3 Do not pay water bill
- 4 Program skip
- 5 Don't know, why?
- 6 Refused, why?

APPENDIX C

CONFIDENCE SCORE AND HETEROSKEDASTICITY

Table C1. Breusch-Pagan Test

Variable	Full Model		OLS Model		Interval Model	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Arsenic Concentration	1.62×10^{-6}	0.328	2.10×10^{-6}	0.20	8.31×10^{-7}	0.828
Public	0.000083*	0.093	0.0000965**	0.044	0.0000691	0.563
Male	0.000015	0.584	0.0000225	0.421	0.0000104	0.871
Years in Current Residence	-1.12×10^{-7}	0.925	-1.80×10^{-6}	0.127	3.53×10^{-6}	0.204
Never Smoker	-0.0000443	0.148	-0.0000541*	0.07	-0.0000568	0.452
Current Smoker	0.0000358	0.416	0.0000553	0.201	-0.000043	0.686
Health Status	0.0000401***	0.005	0.000049***	0.0001	0.0000146	0.676
Confidence Score	-2.13×10^{-7}	0.643	-1.29×10^{-7}	0.772	-2.84×10^{-7}	0.808
N	289		190		99	
Adjusted R ²	0.0426		0.1262		0.0451	

Notes: *, **, *** indicate p-values < 0.1, 0.05, and 0.01. Table C1 reports the result of a Breusch-Pagan test. Dependent variable is the squared residuals pooled from perceived risk models. I speculate the confidence score is related to the heteroskedasticity of perceived risk. The p-values of *Confidence Score* are 0.643, 0.772 and 0.808 in all three models, which suggests that *Confidence Score* has trivial influence on heteroskedasticity.

Table C2. Perceived Risk Models with Heteroskedasticity-Robust Standard Errors

Variable	Full Models (with confidence score)	
	OLS Model	Interval Model
Constant	-0.011 (0.035)**	0.00017 (0.95)
Arsenic Concentration	0.00016 (0.067)*	-0.00002 (0.70)
Public Water System	0.0076 (0.002)***	0.0013 (0.374)
Male	-0.00099 (0.462)	0.002 (0.002)***
Year in Current Residence	-0.000077 (0.123)	0.0001 (0.02)**
Health Status	0.0028 (0.001)***	0.00009 (0.87)
Never Smokers	-0.002 (0.159)	-0.00005 (0.944)
Current Smokers	0.007 (0.036)**	0.0019 (0.298)
Confidence Score of Perceived Risk	0.00002 (0.464)	0.000007 (0.694)
N	190	99
Adjusted R ²	0.215	
Log-likelihood		-174.94

Notes: P-values in parentheses. *, **, *** indicate p-values < 0.1, 0.05, and 0.01.

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